# **SRHE** Society for Research into Higher Education

# Access to attainment: What are the responsibilities of universities towards their diverse student communities? An exploration of the relationship between module characteristics and module mark differences between student ethnic groups Research report

June 2021

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Disclaimer: The views expressed in this report are the authors' and do not necessarily reflect those of the Society for Research into Higher Education

# **Acknowledgements**

We would like to thank the Society for Research into Higher Education (SRHE) for funding and supporting this project.

We would also like to thank Dr Mary Deane, who was instrumental in setting up the project as a member of the original research team.

We are also grateful to Dr Camille Kandiko Howson for her support and advice as our critical friend.

Finally, we would like to thank colleagues in IT Services and Planning who very kindly and very patiently assisted us with data extraction.

# **Executive summary**

A long standing issue in UK higher education (HE) has been the Black and minority ethnic (BAME) awarding gap, which refers to the lower rate of first or 2:1 degrees awarded to BAME students compared to White students. There is an increased recognition of the need for universities to examine institutional practices and to take action to address the awarding gap. This study investigates the relationship between module characteristics and module mark differences between students from different ethnic groups, and introduces a new method of utilising the data that universities already routinely collect in order to better understand awarding differences.

Using this novel method, the *t*-statistic (referred to here as the difference index or DI) is used to represent group differences. DI is preferable to calculating a simple difference of means as it also takes into account group size and score variation. The calculation is straightforward and uses figures easily obtainable from university databases (i.e. the number of students per group, mean mark and standard deviation). In the method described, one DI value was calculated per module per ethnic group comparison (e.g. White v Black, White v Asian, etc.). Multiple regression (enter method) was used to investigate whether module characteristics could predict DI values in a sample of modules taken from two faculties in a post-92 university from the 2015/16 academic year. Key findings and recommendations are as follows.

#### Key findings

- Different results were found for different student groups—only the regression model for the White v Black comparison reached significance. This highlights the importance of recognising the heterogeneity of student experiences and needs.
- For the White v Black comparison, Faculty and Level significantly predicted DI. The former suggests disciplinary differences in module mark gaps, while the pattern noted for the dummy variables representing Level suggested that module mark differences between Black and White narrowed with each successive level (i.e. the gap was the largest at Level 4 and smallest at Level 6).
- Capstone modules (commonly final year project modules) had, on average, smaller DI values compared to non-capstone modules. This finding is similar to a previous investigation on final year undergraduate research projects, where it was noted that students tended to do better on these modules compared to other final year modules (Parker, 2018).

#### **Recommendations for future research areas**

• Future research could replicate the method used in this study to examine the relationship between module characteristics and module mark gaps in other

universities. Multilevel modelling could be used to investigate data from multiple universities or academic years.

Based on the present study's findings, a number of potential areas for future research were identified. These pertained to: (a) a comparative examination of the learning experiences of Level 4, 5 and 6 students from different ethnic groups; (b) whether there is a relationship between module difficulty (e.g. as characterised by the proportion of higher order learning outcomes based on Bloom's (1956) taxonomy) and module mark gaps; and (c) what good practices can be adopted from capstone modules to help address the awarding gap.

# Practical recommendations for researchers interested in conducting similar analyses:

- Prior to investigation, check that it is possible to obtain the required data within a suitable time frame. Bear in mind specific ways you will need to filter or disaggregate your data.
- If investigating a recent academic year, check that the data is up-to-date (e.g. to account for resit data or marks from students with extensions).
- If investigating multiple academic years, check that data has been recorded consistently in all academic years (e.g. ethnic categorisation may have changed).
- If using data from multiple institutions, ensure that comparable data can be obtained. Having a precise plan of what data to collect will prevent issues with missing data (at analysis) and collecting more data than will actually be used.

# Recommendations for universities regarding student data storage and management:

- Student performance data should ideally be able to be filtered by student characteristics (e.g. ethnicity, mode of study, domicile, young/mature status, etc.) and curriculum-related characteristics (e.g. faculty, level, credit, etc.).
- Data from multiple modules and students should be able to be viewed (and exported) at once. The order of cases (whether modules or students) should ideally be pinned so they remain in the same order even as different filters are applied, facilitating data extraction for multiple groups.
- Clear guidance materials for staff using the database should be produced. Ideally, these would explain all terms, button functions, and how scores are filtered and calculated. Security permissions should also be explained here (e.g. what staff can and cannot do with the data, whether permissions change for staff conducting research who have ethical clearance).

### Literature review

The UK higher education (HE) system has yet to address its long standing BAME (Black and minority ethnic) awarding gap, which refers to the lower rate of 'good' (i.e. first or 2:1) degree attainment that UK-domiciled BAME students are awarded relative to their white peers (UUK & NUS, 2019). An early large-scale report which examined data from 65,000 undergraduate qualifiers in the 2004/5 academic year found that ethnicity was significantly related to final degree classification, even after controlling for other factors such as prior educational attainment, type of institution attended and socioeconomic status (Broecke & Nicholls, 2007). Recent data from the Higher Education Statistics Agency (HESA) showed that in the 2018/19 academic year, 82.6% of White, full-time, UK-domiciled first degree qualifiers received a 'good' degree, compared to 61.7% of Black qualifiers and 72.1% of Asian students (HESA, 2020). There is little evidence to suggest that this gap is closing, which suggests that interventions to address it are not working.

The body of quantitative research into the BAME awarding gap offers a useful overview of the scale and extent of the issue. These studies have furthered current understanding of the relative importance of various student and institutional characteristics in explaining final degree outcome for undergraduate qualifiers nationwide (Broecke & Nicholls, 2007; Fielding et al., 2008; Richardson, 2008). A key finding is that membership to a minority ethnic group significantly predicts lower degree attainment, even when controlling for factors like prior attainment, socioeconomic status, disabled status, disciplinary area and type of institution (amongst others) (e.g. Broecke & Nicholls, 2007). These studies also highlight the nuances of the BAME attainment gap: different student characteristics, such as age, disability status and the disaggregated ethnic categories with which students identified varied in the extent to which they were linked with final degree classification (Broecke & Nicholls, 2007; Fielding et al., 2008). Findings from these studies attest to the complex and pervasive nature of the BAME awarding gap for UK HE.

While it is clear that BAME students have systematically lower outcomes than their peers, there is less certainty around the reasons for this (Richardson, 2015). Ongoing research into the HE experiences of BAME and non-traditional students has identified a number of possible contributory factors. Earlier work tended to focus on factors pertaining to the student, for instance financial barriers (Gorard et al., 2006, Thomas, 2002), attitudes towards HE (Ball et al., 2002; Bamber & Tett, 2000), the use of English as an additional language (Berry & Loke, 2011; Cotton et al., 2016; Gorard et al., 2006) and the (re-)negotiation of class and learner identities (Reay et al., 2010). More recent research has shifted away from student characteristics towards factors related to the impact of institutional practices, for instance microaggressions and the lack of belonging experienced by BAME students (Bunce et al., 2019; Smith, S. V., 2017; Stevenson, 2018; Wong et al., 2020), the types of feedback received by students of different ethnic

groups (Richardson et al., 2015), and the predominance of White, middle class practices and norms in HE (Bird & Pitman, 2019; Madriaga & McCaig, 2019). This shift towards factors related to students' university experiences—which are, to a much greater extent, within the control of universities—is in line with increasing recognition that a deficit approach (which identifies students as responsible for the BAME awarding gap; UUK & NUS, 2019) overlooks the likely systemic causes of the BAME awarding gap. Indeed, the recent introduction of the term *awarding gap* (e.g. Jankowski, 2020) as opposed to *attainment gap* is evidence of a growing recognition of universities' responsibilities in addressing the issue.

However, institutional responsibility tends to be viewed holistically; still little is known about the relationship between academic practices at specific (e.g. course or module) levels and the BAME awarding gap. An investigation by Parker (2018) on final year independent research projects (e.g. dissertations) found that students scored more highly on these capstone modules compared to other final year modules. Parker referred to this as research gain and identified a number of factors which significantly predicted the extent of a student's research gain. One predictor was Asian ethnicity, which predicted a smaller research gain relative to White ethnicity: controlling for all other variables, the research gain for an Asian student was 1.36 marks lower than that for a White student (note: no significant effect of Black ethnicity was reported) (ibid.: 155). Another significant predictor was prior attainment (operationalised as the average mark of a student's other final year modules), which had a negative relationship with research gain: controlling for all other variables, a ten mark decrease in prior attainment was associated with a 0.85 mark increase in research gain. In other words, a student with a lower average mark for their (non-capstone) final year modules would do better on their independent research project (relative to the rest of their final year modules) (ibid.: 154).

Parker's investigation provides insight into how module-level practices might be linked to the awarding gap. There remains, however, little investigation of the mechanism of the awarding gap at a granular level, in relation to the module-level experiences of students from different ethnic backgrounds, across disciplines and levels of study. This study seeks to address this gap by investigating whether module characteristics (e.g. level, credit value, learning outcomes, etc.) can predict differences in the module marks awarded to students from different ethnic backgrounds. This study aims to contribute to sector-wide understanding of what universities can do to address the BAME awarding gap.

# Method

### **Overall analytical approach**

Multiple regression (enter method) was used to investigate the relationship between module characteristics (the predictor variables) and differences in module marks between ethnic groups (the outcome variable). As the outcome variable was a measure of difference between two groups, one regression model was computed for each comparison (e.g. White v Asian, White v Black, etc., noting that ethnic categories were not able to be further disaggregated due to small numbers). This enabled investigation of whether different characteristics dis/advantaged minority ethnic groups in different ways, relative to White students.

The enter method for variable selection was used in the building of the regression models. Using this method, all predictor variables are entered into the model simultaneously. This is in contrast to other variable selection methods where predictor variables are entered into (or removed from) a model sequentially, either manually or based on purely mathematical considerations. The enter method was chosen as it allows for a neutral starting point from which to examine the individual contributions of each predictor variable, and was thus deemed the most suitable considering the exploratory nature of the analysis (Smith, G., 2018; Studenmund & Cassidy, 1987).

#### Module scores and characteristics

Undergraduate module scores from the 2015/16 academic year from two faculties at a post-92 university were extracted from centrally held records. Only module scores from young (i.e. not mature), full-time, UK-domiciled students were included. Modules qualified for analysis if at least three White students *and* at least three students from at least one other ethnic category were enrolled (note that only young, full-time, UK-domiciled students were included in these calculations). Due to small numbers and associated issues of data protection, ethnic categories were not fully disaggregated. The ethnic categories used in the analysis were thus White, Asian, Black, Mixed and Other. Data from resits (which are capped at 40%) was included. For each module, the following figures were extracted for every ethnic group which had at least three qualifying students (i.e. young, full-time, UK-domiciled): the number of students, their average module score and the standard deviation. It should be noted that as modules did not always have three qualifying students from every ethnic group, modules did not necessarily appear in every regression model.

Data on the modules' characteristics were then manually extracted from a separately held module information directory (MID), which is completed for all modules and contains

required fields, such as a descriptor, coursework weighting, indication of prerequisites, learning outcomes, and a detailed breakdown of teaching activities (including lectures, workshops, self-guided time, etc.). These characteristics were used as predictor variables in the regression analyses. The list of characteristics and how they were operationalised are below. Other module activities (e.g. laboratory hours, workshop hours) were considered but ultimately excluded from analysis due to uneven distributions in the hours listed (e.g. most modules listing 0 hours).

- (a) Faculty. Which faculty a module was associated with.
- (b) Level. Dummy coded with Level 4 as the baseline group.
- (c) *Has Prerequisite*. Modules were coded as having prerequisites if this information was specifically stated in the relevant mandatory MID field.
- (d) *Exam Weight.* The percentage of the total module score assessed via examination(s) as opposed to coursework.
- (e) *Lecture Hours.* The number of hours students were expected to spend in lectures, as listed on the relevant MID.
- (f) *Self-guided Hours.* The number of hours students were expected to spend on self-guided study, as listed on the relevant MID.
- (g) *Higher Order Learning Outcome (HOLO) Proportion.* The percentage of learning outcomes listed on a module's descriptor which corresponded with the last three domains in Bloom's (1956) taxonomy (analysis, synthesis and evaluation).

In addition to the above, separate descriptive analyses were undertaken for a further three variables which are listed below. The decision was made to exclude these variables from regression modelling due to very uneven distributions of modules between the levels of these variables.

- (h) Credit Value. Modules were either 10, 20 or 30 credits.
- (i) *Capstone*. Final year projects, dissertations and synoptics were coded as capstone modules.
- (j) *Group Assessment.* Whether or not a module had a group assessment component.

#### The difference index

The awarding gap between ethnic groups was operationalised with what will be referred to as the difference index (DI). The DI is a score which reflects the difference between the average mark of two groups on a particular module, taking into account each group's size and module mark variation. The formula for calculating DI is below (note that the DI is in fact the *t*-statistic, but will be referred to as the DI to avoid confusion with the *t*-

values computed as part of the regression analyses). Here, *n* is the number of students in a group, *s* is the standard deviation, and  $\bar{x}$  is the group mean.

$$DI = \frac{\bar{x}_{A} - \bar{x}_{B}}{\sqrt{\frac{s_{pooled}^{2}}{n_{A}} + \frac{s_{pooled}^{2}}{n_{B}}}}$$
$$s_{pooled}^{2} = \frac{(n_{A} - 1) s_{A}^{2} + (n_{B} - 1) s_{B}^{2}}{n_{A} + n_{B} - 2}$$

A larger absolute value indicates a larger difference in module mark between two groups. A positive DI means that the baseline group outperformed the comparison group on average, while a negative DI means that the comparison group outperformed the baseline group on average. In this analysis, the baseline group was always White students, and comparison groups were either Asian, Black, Mixed or Other students. It should be noted that as the DI is scaled to group sizes and module mark variation, it is not easily interpretable in terms of actual module mark differences. However, as an illustration, for two groups each with 10 students and an equal spread of scores (SD = 10.00; note that this value is similar to that observed in the sample), a difference of 5 marks would give a DI value of 1.12 and a difference of 10 marks would give a DI value of 2.24.

## **Findings and discussion**

#### Sample breakdown and descriptive statistics

The overall sample contained 59 modules. Of these, 23 were from Faculty1 and 36 from Faculty2. There were 26 Level 4 modules, 15 Level 5 modules and 18 Level 6 modules. Most of the modules (51) were worth 20 credits, while seven were worth 10 credits and one was worth 30 credits. Two modules were capstone modules and four modules involved some form of group assessment. There were 37 modules which did not have a prerequisite and 22 which did. The exam weights of modules ranged from 0-100 percent, averaging at 19.15 percent (SD = 31.45). Modules had between 0 and 50 lecture hours (M = 19.88, SD = 12.76), and between 0 and 235 self-guided hours (M = 97.31, SD = 12.76)47.50). The mean HOLO proportion was 39.77% (SD = 31.10).

Turning to the mean marks of student groups for the modules in the sample, the mean mark for White students was the highest on average (M = 61.55, SD = 7.95). This was followed by Asian and Other students who had similar mean marks, roughly five marks lower than the White mean (for Asian students, M = 57.79, SD = 7.33; for Other students, M = 55.72, SD = 7.34). The lowest mean marks were observed for Black and Mixed students (for Black students, M = 52.64, SD = 6.15; for Mixed students, M = 52.96, SD =5.65). These patterns were also reflected in the DI values, with the largest average DI values reported for the White v Black and White v Mixed comparisons (see Table 1).

| modules in each comparison. |    |       |      |       |       |
|-----------------------------|----|-------|------|-------|-------|
|                             | n  | М     | SD   | Min.  | Max.  |
| Mean module mark            |    |       |      |       |       |
| White                       | 59 | 61.55 | 7.95 | 45.18 | 79.13 |
| Asian                       | 59 | 57.79 | 7.33 | 41.84 | 74.86 |
| Black                       | 52 | 52.64 | 6.15 | 38.73 | 62.74 |
| Mixed                       | 18 | 52.96 | 5.65 | 44.67 | 65.33 |
| Other                       | 26 | 55.72 | 7.34 | 41.58 | 69.60 |
| DI                          |    |       |      |       |       |
| White v Asian               | 59 | 0.80  | 1.24 | -2.24 | 3.28  |
| White v Black               | 52 | 1.86  | 1.37 | -1.11 | 5.15  |
| White v Mixed               | 18 | 1.34  | 0.60 | -0.17 | 2.17  |
| White v Other               | 26 | 0.64  | 1.40 | -1.64 | 4.60  |

Mean module mark (by ethnic category) and DI of

Table 1.

### **Regression analyses**

#### White v Asian

A multiple regression (enter method) was conducted to determine whether module characteristics (Faculty, Level, Has Prerequisite, Exam Weight, Lecture Hours and Self-guided Hours, HOLO Proportion) could predict module mark differences (as measured by DI) between White students and Asian, Black, Mixed or Other students. For the White v Asian comparison, the model included 59 modules. The model did not reach significance, F(8, 50) = 0.83, p = .58, suggesting that there was no relationship between the module characteristics examined here and module mark differences between White and Asian students.

#### White v Black

The multiple regression (enter method) model computed for the White v Black comparison included 52 modules. The model was able to explain 32.8% of variance in the DI values and this was statistically significant F(8, 43) = 4.11, p < .005. The regression model satisfactorily met the assumptions of homoscedasticity, no multicollinearity, and independent and normally distributed errors. There were also no outliers or cases with undue influence on the model. The module characteristics which significantly predicted DI were: Faculty (B = -0.97, p < .05), Level 5 relative to Level 4 (B= -1.01, p < .05) and Level 6 relative to Level 4 (B = -1.66, p < .005). The significance of the Faculty variable suggests that, perhaps unsurprisingly, there were disciplinary differences in the extent of the module mark gap between White and Black students. The negative regression coefficients found for the Level 5 and Level 6 dummy variables, and further that the regression coefficient for Level 6 was the larger (in absolute value) of the two, suggests that the module mark gap between White and Black students becomes progressively smaller with each year. A follow-up examination of mean scores for White and Black students by level showed that on average, White students improved between Level 4 and 5 while slightly dipping between Level 5 and 6, whereas Black students improved with each successive level (though Black student means were nevertheless lower than those of White students at all levels).

The remainder of the predictor variables (Has Prerequisite, Exam Weight, Lecture Hours, Self-guided Hours and HOLO Proportion) did not reach significance, suggesting that these were not related to the module mark gap between White and Black students.

#### White v Mixed

The multiple regression (enter method) model computed for the White v Mixed comparison included 18 modules. An examination of the distribution of modules across

the levels of the predictor variables revealed that there were no Level 5 modules. Additionally, multicollinearity diagnostics showed a strong and significant relationship between Faculty and Exam Weight, r = -.85, p < .001 (one-tailed). Thus, the dummy variable for Level 5 and the Faculty variable were excluded from the regression model. The model did not reach significance, F(6, 11) = 1.24, p = .36. This suggests that there was no relationship between the module characteristics examined in the model and differences in module mark between White and Mixed students.

#### White v Other

The multiple regression (enter method) model computed for the White v Other comparison included 26 modules. An examination of the distribution of modules across the levels of the predictor variables revealed that there were no Level 5 modules. The dummy variable for Level 5 was thus not included in the analysis. The model did not reach significance, F(7, 18) = 0.89, p = .54, indicating that no relationship between the module characteristics and differences in module mark between White and Other students.

#### Analysis of Credit Value, Capstone and Group Assessment

Due to the very uneven distribution of modules across the levels of the variables Credit Value, Capstone and Group Assessment, the decision was made to exclude these variables from the regression model and instead analyse them separately to inform future work. The DI values for all four comparisons were examined using these predictors as grouping variables (see Table 2).

#### Table 2.

| Croup / loocoomoni. |    |      |      |       |      |
|---------------------|----|------|------|-------|------|
|                     |    | DI   |      |       |      |
|                     | n  | М    | SD   | Min.  | Max. |
| Credit Value        |    |      |      |       |      |
| White v Asian       |    |      |      |       |      |
| 10 credits          | 7  | 0.89 | 1.28 | -0.76 | 2.58 |
| 20 credits          | 51 | 0.79 | 1.26 | -2.24 | 3.28 |
| 30 credits*         | 1  | -    | -    | -     | -    |
| White v Black       |    |      |      |       |      |
| 10 credits          | 6  | 1.17 | 0.87 | 0.00  | 2.17 |
| 20 credits          | 45 | 1.97 | 1.41 | -1.11 | 5.15 |
| 30 credits*         | 1  | -    | -    | -     | -    |
| White v Mixed       |    |      |      |       |      |
| 10 credits          | 4  | 1.08 | 0.41 | 0.59  | 1.45 |
| 20 credits          | 14 | 1.41 | 0.64 | -0.17 | 2.17 |

DI values of modules grouped by Credit Value, Capstone and Group Assessment.

| White v Other<br>10 credits<br>20 credits | 5<br>21 | 0.89<br>0.59 | 0.62<br>1.54 | 0.15<br>-1.64 | 1.65<br>4.60 |
|---|---------|--------------|--------------|---------------|--------------|
| Capstone                                  |         |              |              |               |              |
| White v Asian                             |         |              |              |               |              |
| No  | 57      | 0.82         | 1.24         | -2.24         | 3.28         |
| Yes                                       | 2       | 0.07         | 1.10         | -             | -            |
| White v Black                             |         |              |              |               |              |
| No  | 50      | 1.91         | 1.37         | -1.11         | 5.15         |
| Yes                                       | 2       | 0.58         | 0.57         | -             | -            |
| White v Mixed                             |         |              |              |               |              |
| No  | 17      | 1 33         | 0.62         | -0 17         | 2 17         |
| Yes                                       | 1       | -            | -            | -             | -            |
|   | -       |              |              |               |              |
| White v Other                             |         |              |              |               |              |
| No  | 25      | 0.66         | 1.43         | -1.64         | 4.60         |
| Yes                                       | 1       | -            | -            | -             | -            |
| Group Assessment                          |         |              |              |               |              |
| White v Asian                             |         |              |              |               |              |
| No  | 55      | 0.78         | 1.25         | -2.24         | 3.28         |
| Yes                                       | 4       | 1.03         | 1.20         | -0.22         | 2.31         |
|   |         |              |              |               |              |
| White v Black                             | 40      | 4.00         | 4.00         |               |              |
| NO<br>Voo                                 | 49      | 1.83         | 1.39         | -1.11         | 5.15         |
| res                                       | ა       | 2.37         | 1.11         | 1.52          | 3.03         |
| White v Mixed                             |         |              |              |               |              |
| No  | 17      | 1.31         | 0.60         | -0.17         | 2.17         |
| Yes                                       | 1       | -            | -            | -             | -            |
| White v Other                             |         |              |              |               |              |
| No  | 23      | 0.50         | 1.14         | -1.64         | 3.71         |
| Yes                                       | 3       | 1.74         | 2.86         | -1.12         | 4.60         |

\*Values not shown for anonymity.

First, for Credit Value, there was considerable overlap between the DI values for the 10, 20 and 30 credit modules for all four comparisons. This suggests that credit value is not linked with module mark gaps. Similarly, for Group Assessment, modules with group assessments had a higher DI value on average than modules which did not; however, there was considerable overlap in the DI values of modules with and without group assessment, suggesting no relationship between the presence of group assessments and module mark gaps.

For the Capstone variable, average DI values were noticeably smaller for capstone modules compared to non-capstone modules (with the exception of the White v Mixed comparison). This suggests that module mark gaps are smaller in capstone modules compared to non-capstone modules. This is consistent with Parker's (2018) findings that students scored more highly on independent research projects compared to their other final year modules, a phenomenon which Parker referred to as research gain. Additionally, Parker found that Asian ethnicity (relative to White ethnicity) predicted lower research gain, while no significant effect of Black ethnicity was found. Parker's findings, together with the present finding, suggest that not only do students as a whole do better on capstone modules than other final year modules, module mark gaps between ethnic groups may also be narrowed in capstone modules.

## **Conclusions and recommendations**

This study investigated whether module characteristics could predict ethnic differences in module marks awarded in a post-92 university. This section discusses key findings and insights from the study, organised into two broad areas: pedagogical practices and practical considerations for researchers and universities around data analysis and management.

### **Pedagogical practices**

Different results were found for different student groups—only the regression model for the White v Black comparison reached significance. This highlights the importance of recognising the heterogeneity of student experiences and needs. For the White v Black comparison, Faculty and Level significantly predicted DI. The significance of the Faculty variable suggests that there are disciplinary differences in module mark gaps between White and Black students. The larger negative effect found for the Level 6 dummy variable compared to that for Level 5 (both relative to Level 4) suggests that module mark differences narrowed as students progressed through university. At least for this university, more targeted support for Black first year students would help to address module mark differences relative to White students early on. An interesting finding was that HOLO Proportion did not significantly predict DI, indicating no evidence of a relationship between a module's difficulty (as represented by HOLO Proportion) and module mark differences between White and Black students. It would be interesting to further explore whether this finding is replicated across the sector.

A final point concerns the finding that capstone modules had, on average, noticeably smaller DI values compared to non-capstone modules for all comparisons, apart from White v Mixed. Parker (2018) notes that undergraduate capstone research projects are a 'high impact' (p. 145) pedagogic practice, though their learning benefits have received disproportionately little scholarly attention. It would be worth examining what practices specific to capstone modules might help to reduce module mark differences between ethnic groups. Investigations should consider both pedagogical practices (e.g. around marking) and students' learning experiences. For the latter, based on insights from research about the experiences of BAME students (Bunce et al., 2019; Smith, S. V., 2017), some possibilities include the relatively high amount of one-to-one support received and the freedom to choose one's topic (at least in some disciplines) which facilitates a greater sense of autonomy and motivation.

#### Practical considerations for researchers and universities

The researchers faced barriers obtaining data for the present analysis. This subsection presents practical insights for those wishing to conduct similar investigations, whether within their own institutions or in cross-institutional projects, as well as to institutions seeking to improve how student data is captured and organised.

The first difficulty was that institution-wide module-level data were not directly accessible to academic staff (marks were extracted on behalf of the researchers by the team managing the database). The inaccessibility of this data prevents staff from understanding first-hand and in a timely manner awarding differences at a local level (e.g. on the modules they teach) and may hinder understanding of wider institutionallevel awarding patterns. The UUK and NUS (2019: 56-7) emphasised the important role of clear, granular institutional data in understanding and addressing the awarding gap. From the researchers' experiences, infrastructural limitations rather than privacy concerns were the main barriers to accessing useful data (note that the project was originally planned to have data from two institutions; explained further below). Thus poor data storage practices may be limiting universities' self-assessment capabilities. Ideally, student performance data would be accessible locally and filterable by student characteristics (e.g. ethnicity, mode of study, domicile, young/mature status, etc.), alongside module-related information. Permissions around data security and privacy should also be made clear to staff. To facilitate institutional-level analysis, data from multiple modules/students should be able to be viewed (and exported) at once. This would enable the data to be explored in many ways, for instance by module (as this study has done) and by using within-subject designs that can examine, for instance, how the same students (or groups of students) perform across different modules and types of assessments.

For those interested in conducting analyses similar to the present study, it would be useful to check whether the desired data can realistically be obtained. As alluded to above, data were unobtainable from one of the two institutions in the original plan. For this institution, the start of the project coincided with a major update to the relevant university database, which itself was disrupted by the onset of the Covid-19 pandemic in the UK. Researchers interested in carrying out similar analyses should liaise with relevant colleagues to ensure that it will be possible to obtain data within the required time frame (barring unexpected external factors). For those interested in inter-institutional collaborations, some practical considerations to bear in mind include: securing necessary data sharing agreements; ensuring that comparable data can be obtained, as there may be institutional differences in how modules or programmes are organised, as well as how student performance data is stored and in what specific ways it can (and cannot) be filtered or disaggregated. Relatedly, if small sample sizes are a concern, planning ahead

so that there are no issues with missing data (at analysis), or so that institutions do not collect more data than will actually be used.

#### Recommendations

Future research could replicate the method used in this study to examine the relationship between module characteristics and module mark gaps in other universities. Multilevel modelling could be used to investigate data from multiple universities or academic years (or potentially both). Other possible areas for investigation pertain to:

- the similarities and differences between the learning experiences of Level 4, 5 and 6 students of different ethnic groups;
- whether there is a relationship between module difficulty (e.g. as characterised by HOLO Proportion) and module mark differences; and
- what good practices can be adopted from capstone modules to help address the awarding gap.

For researchers interested in conducting similar analyses, the following practical recommendations are made:

- Prior to investigation, check that it will indeed be possible to obtain the required data within a suitable time frame. Bear in mind specific ways you will need to filter or disaggregate your data.
- If investigating a recent academic year, check that the data is up-to-date (e.g. to account for resit data or marks from students with extensions).
- If investigating multiple academic years, check that data has been recorded consistently in all academic years (e.g. ethnic categorisation may have changed).
- If using data from multiple institutions, ensure that comparable data can be obtained. Having a precise plan of what data to collect will prevent issues with missing data (at analysis) and collecting more data than will actually be used.

Lastly, recommendations for student data storage and management are as follows:

- Student performance data should ideally be able to be filtered by student characteristics (e.g. ethnicity, mode of study, domicile, young/mature status, etc.) and curriculum-related characteristics (e.g. faculty, level, credit, etc.).
- Data from multiple modules and students should be able to be viewed (and exported) at once. The order of cases (whether modules or students) would ideally be able to be pinned so they remain in the same order even as different filters are applied. This would facilitate data extraction for multiple groups.

• Clear guidance materials for staff using the database should be produced. Ideally, these would explain all terms, button functions, and how scores are filtered and calculated. Security permissions should also be explained here (e.g. what staff can and cannot do with the data, whether permissions change for staff conducting research who have ethical clearance).

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